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Modified Artificial Potential Fields Algorithm for Mobile Robot Path Planning

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Abstract— The problem of path planning is studied for the case of a mobile robot moving in an environment filled with obstacles whose shape and positions are not known. Path planning is dynamic when the path is continually recomputed as more information becomes available. A computational framework for dynamic path planning is proposed which has the ability to provide navigational directions during the computation of the plan. Path planning is performed using a potential field approach. This paper introduces a new algorithm, bidirectional artificial potential fields, capable of planning paths in unknown, partially known, and changing environments in an efficient, optimal, and complete manner. The algorithm uses the potential field values iteratively to find the optimum points in the workspace in order to form the path from start to destination. In the algorithm, motion planning is done continuously (dynamically), based on the system's current position and on its feedback.
Keywords— Mobile robot, Path Planning, Artificial Potential Field, Collision Free Path

I. INTRODUCTION

Obstacle avoidance is one of the key issues to successful application of mobile robot systems. Based on the configuration space and the destination generating a path (finding a continuous route) in a 2D environment with unknown obstacles represent still a fundamental problem to be solved.

The abominable and potentially dangerous objects encountered by the robot in its route to destination are the obstacles and must be avoided. The capacity to move without collision in the uncertain environment taking into consideration the perception of the system is a fundamental problem to be solved in the autonomous mobile robot field. We study the problem of robust navigation for indoor mobile robots.

Numerous algorithms and methods have been proposed for path planning of mobile robots. Artificial potential fields (APF) are the method most widely used due to its mathematical simplicity and ease of implementation and high efficiency. The Artificial potential field method was proposed by Khatib, which is a virtual force field method [8]. The basics of artificial field method are finding a function that represents the energy of the system and forces the robot to move towards the destination which possesses the minimum energy value [5]. The robot is made to travel from high-potential to low-potential state. Moving the robot from source point to the destination in a 'downhill approach' is mathematically termed as the gradient descent (i.e.)

$$x = x_k - \lambda \Delta f(x_k) \qquad (1)$$

The motion terminates as the gradient vanishes. Although these methods are fast and efficient, they have the following drawbacks and limitations as discussed in [13]:

a) Trap situations due to local minima.
b) No passage between closely spaced obstacles.
c) Oscillations in the presence of obstacles.
d) Oscillations in narrow passages.
e) Incapability to avoid dynamic obstacles.

While trying to solve the above stated problems, researchers have introduced an additional potential so that the destination becomes the global minima. Still others have made changes to the path and tried to avoid the minimum points. A few researchers have tried to incorporate artificial intelligence methods into the potential methods.

The aim of this paper is to use the artificial potential field method to detect and avoid the static as well as the dynamic obstacles. The navigation architecture is made of a global planner, local planner and a cost map. Localization of the robot is done with the visualization obtained from amcl. The proposed algorithm was implemented in the robot operating system (ROS), a LINUX based framework used for controlling robots. The reminder of the paper is arranged as follows: section1 discusses the algorithm for sensing and avoiding the static obstacles. Section 2 examines the performance of this method through simulations. In section 3, new APF based method for dynamic path planning is explained. Finally section 4 discusses the time and space complexity with section 5 providing the conclusions and further work.

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II. STATIC OBSTACLE AVOIDANCE

Since the model under study is a mobile robot possessing freedom along the X and Y and rot (rotation about Z) motion, the gross workspace is a 2D space. Each point of the workspace is considered and the potential at each point is determined. The notion of cell is introduced for further use in this paper which represents each pixel point in the camera transformation matrix. The workspace is considered to be a discrete space of N coordinate cells X=(x, y) and each cell is either obstacle or free space.
The potential is given as

$$U_{Total}(x)=U_{source}(x)+U_{destination}(x)-U_{Obstacle}(x) \quad [1] \qquad (2)$$

The individual terms are expressed as

$$U_{source}(x) = \varrho/D(x, a) \qquad (3)$$

$$U_{destination}(x) = \varrho/D(x, b) \qquad (4)$$

$$U_{Obstacle}(x) = \gamma/D(x, c) \qquad (5)$$

Where, $D(x, a)$ is the Euclidean distance between the locations of robot and the cell. $D(x, b)$ is the Euclidean distance between the destination of robot and the cell. $D(x, c)$. is the minimum distance between the affected areas of obstacle and the location of the robot. ϱ and γ, the gain's coefficients of attraction and repulsion functions respectively are positive constants.
Using the expression (2) the potential for each cell in the workspace is determined. These determined potentials are then sorted in descending order. The cells with high potential are found to occupy positions close to the source point and destination point. Of the sorted potentials, the top 60% is considered to determine the threshold value, a notion to be continued for the rest of the paper. A threshold value is picked from the sorted list and all the cells with potential values greater than the threshold is studied. If the set threshold value is large, two distinct clusters of marked cells around start and destination points is obtained. As the threshold value is gradually decreased, these two clusters get bigger and bigger until they run into each other
The threshold values are altered until a particular value is reached that guarantees that there is one and only one cell that connects the source point cluster to the destination point cluster. Values smaller than this threshold value would make a connection between two clusters, but this threshold value is the biggest value that by using all cells with potential value bigger than this value makes it possible for having a path between start and end points. The point that connects these clusters is called the midpoint. It is observed that, there is a path from the start point to the midpoint, and there is a path from midpoint to the destination within the range of the clusters. This is implementing by using the breadth first search algorithm.
The next step is to find the midpoint between the source and the current midpoint assuming that only a few cells of the workspace are available. This process is iteratively repeated until a straight line path exists between consecutive points.

III. SIMULATION RESULTS

Two examples with two different environments are studied. If a collision is detected, the robot due to the prime repulsive force is deviated. Using this method, a smooth path with reasonable distance form obstacles is identified while keeping the path as short as possible. The algorithm has been simulated in the ros4mat an open source client/server library which supports the Kinect interface. Ros4mat allows a platform independent connection between the robot and multiple clients.

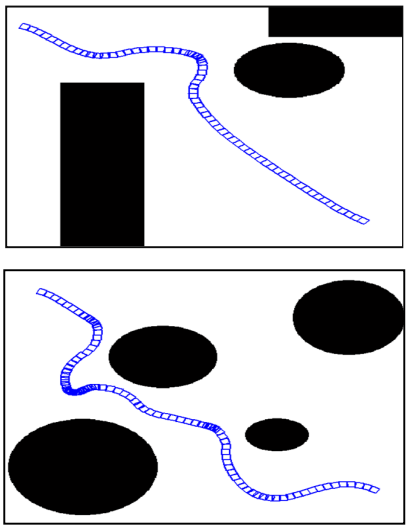


Fig. 1 Simulation Results of Static Obstacle Sensing

IV. DYNAMIC OBSTACLE AVOIDANCE

The proposed algorithm is based on the principles of APF path planning and our proposed ideas. These ideas are suggested to avoid collision with moving entities and to ensure a reliable on-line path planning where the robot employs continuous sensing and acting. The proposed algorithm is presented as a sequence of following steps.

A. Analysis of Obstacle Behaviour

First step in the analysis of behaviour of dynamic objects is learning from the data obtained about their previous states. The most basic conceptualization of a moving object's space–time behaviour is a geo-spatial lifeline [4] – also referred to as a movement path or trajectory, which describes a sequence of visited locations in space, at regular or irregular temporal intervals [10]. This process is known as spatiotemporal data mining a field still under persistent research and only limited researchers are working on the human – interface spatial data analysis. Several prediction techniques are used to predetermine the location of moving entities: neural networks ([11][5][7]), Markov models [12] Ehrenfest chains or Kalman filter ([9][3][2]).

B. Markov Models

Though the motion of obstacle is continuous, the imaging and other communication technologies support sampling only at discrete time. These sample datum obtained are analyzed to determine the behaviour of moving entities. A Markov Chain consists of a countable (possibly finite) set S (called the state space) together with a countable family of random variables X_0, X_1, X_2, ... with values in S such that

$$P[X_{l+1} = s \mid X_l = s_l, X_{l-1} = s_{l-1}, \cdots, X_0 = s_0] = P[X_{l+1} = s \mid X_l = s \quad (6)$$

This fundamental equation is referred to as the Markov property.

Consider a autonomous mobile system that may be described at any time as being in one of the N countable states S_0 S_1… S_n. At regularly spaced discrete times, the system undergoes a change of state within the workspace. The time instants associated with the change of state is denoted as t = 0,1,... , and the actual state at time t is given as St [6]. X is a set of stochastic variables $\{X_t, t \in T\}$. The random variables $X_0, X_1, X_2, \ldots$ are dependent. Markov property expresses the assumption that the knowledge of the present *(i.e., Xl = sl)* is relevant to predictions about the future of the system, however additional information about the past $(Xj = sj, j \leq l - 1)$ is irrelevant.

For the following consideration it is assumed that the chains are time-homogeneous:

$$A_{ij} = P(X_{t+1} = i \mid X_t = j) = P(X_t = i \mid X_{t-1} = j), \forall t \in T, \forall i, j \in S. \quad (7)$$

Unless stated to the contrary, all Markov chains considered in this paper are time homogeneous and we simply represent the matrix of transition probabilities as P = (Pij). P is called the transition matrix. The non-homogeneous case is generally called time inhomogeneous or non-stationary in time.

For a homogeneous Markov chain the transition probabilities can then be noted in a time independent stochastical matrix A:

$$A=[a_{ij}], a_{ij} \geq 0 \quad i, j \in S, \Sigma a_{ij} = 1 \quad (8)$$

Where A is called the transition matrix .It can be shown that the probability of getting in m steps to state j, starting from state i

$$a_{ij} = P(X_{t+m} = j \mid X_t = i) \quad (9)$$

can be computed as the m-th power of the transition matrix a_{ij}=A[i,j]. Recapitulating, a first-order time-homogeneous Markov Chain can be defined as a 3-tuple, consisting of the set of states S, the transition matrix A and the initial distribution vector

$$\theta = (S, A, \pi) \quad (10)$$

The embedded-renewal process is considered to determine the time at which the moving entity intrudes the path of the mobile robot. The time of the nth visit to point y is denoted by

$$T_{y,n}=\min\{k \in N+ : Ny,k=n\} \quad (11)$$

The function is expressed as

$$N_{y,n}=\sum i=1n1(X_i=y) \quad (12)$$

Where $N_{y,n}$ is the number of visits

The behaviour of the system thus analyzed from the sampled data and is simultaneously expounded to obtain the accurate time and point of collision. The feedback data obtained from the odometers paired with the mobile robot wheel helps in the localization of the robot

C. Collision Avoidance

It is ensured that the mobile robot avoids the obstacles by passing them with safe potential distance. The analyzed behaviour

determines the exact point of collision of the robot and the obstacle, henceforth providing a time frame in advance to take the necessary precautions. The velocity of the robot can be altered (i.e.) increased or decreased with an allowable scaled factor as measure. This step depends on the velocities of the robot and the obstacles. An alternative proposed method utilizes the earlier calculated potentials. The map at the location of the expected collision point is retrieved from the global map and is further analyzed by applying the iterative midpoint method. Size of the retrieved map depends on the direction of motion and the dimensions of obstacles.

V. TIME AND SPACE COMPLEXITY

The efficiency and the practicality of the algorithm depends on the time and space complexity of execution. To determine the midpoint, all the cells must be sorted according to their threshold value. For this purpose the time is estimated to be $(NLogN)$ and expected memory is (N). Using the breadth first algorithm, it is checked if the destination point is reachable from the start point and for this purpose the time required is (N) and (N) of memory is required. The binary search algorithm can be implemented with a time complexity of $(NLogN)$ and finally the time and memory required for the analysis of behavior is $(NLogN)$. The total time to run the algorithm will be (N^2LogN) and the memory required will be (N) thus proving the algorithm to be time and memory efficient.

VI. CONCLUSION

In this paper, modified artificial potential field algorithm is used to solve the path planning in an unknown and dynamic environment. The simulation results show that the proposed algorithm is fast and efficient. In addition, it overcomes the drawbacks and limitations of traditional artificial potential field. The proposed algorithm has the capabilities like escapes from dynamic obstacles. The variations in the velocity of the obstacle might lead to changes in behaviour and result in collision. As a further work the dynamic path planning in the ROS platform and real time implementation is under study.

REFERENCES

[1]H.Adeli, M.H.N.Tabrizi and A. Mazloomian, "Path Planning for Mobile Robots using Iterative ArtificialPotential Field Method", *IJCSI International Journal of Computer Science,* vol. 4,no. 2, pp. 28-32 , July 2011.

[2]J.Froehlich and J.Krumm, "Route Prediction from Trip Observations", *Society of Automotive Engineers (SAE) World Congress,* 2008.

[3] J.M.François, G.Leduc and S.Martin, "Learning movement patterns in mobile networks: a generic approach', *Proceedings of European Wireless*, pp. 128-134, 2004.

[4] K.Hornsby and M.J.Egenhofer, "Modeling moving objects over multiple granularities", *Annals of Mathematics and Artificial Intelligence*, vol. 36,pp. 177–194, 2002.

[5]K.Uyanik, "A study on Artificial Potential Fields", *KOVAN Research Lab*, 2004.

[6]L.R.Rabiner, "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition", *Proceedings of the IEEE*, vol. 77,1989.

[7]L.Vintan, A.Gellert, J.Petzold and T.Ungerer,"Person Movement Prediction Using Neural Networks", *Workshop on Modelling and Retrieval of Context*, 2004.

[8]M.Mohamed and M.Abbas, "Obstacles Avoidance for Mobile Robot Using Enhanced Artificial Potential Field", *Al-Khwarizmi Engineering Journal,* vol. 9, pp. 80-91,2012.

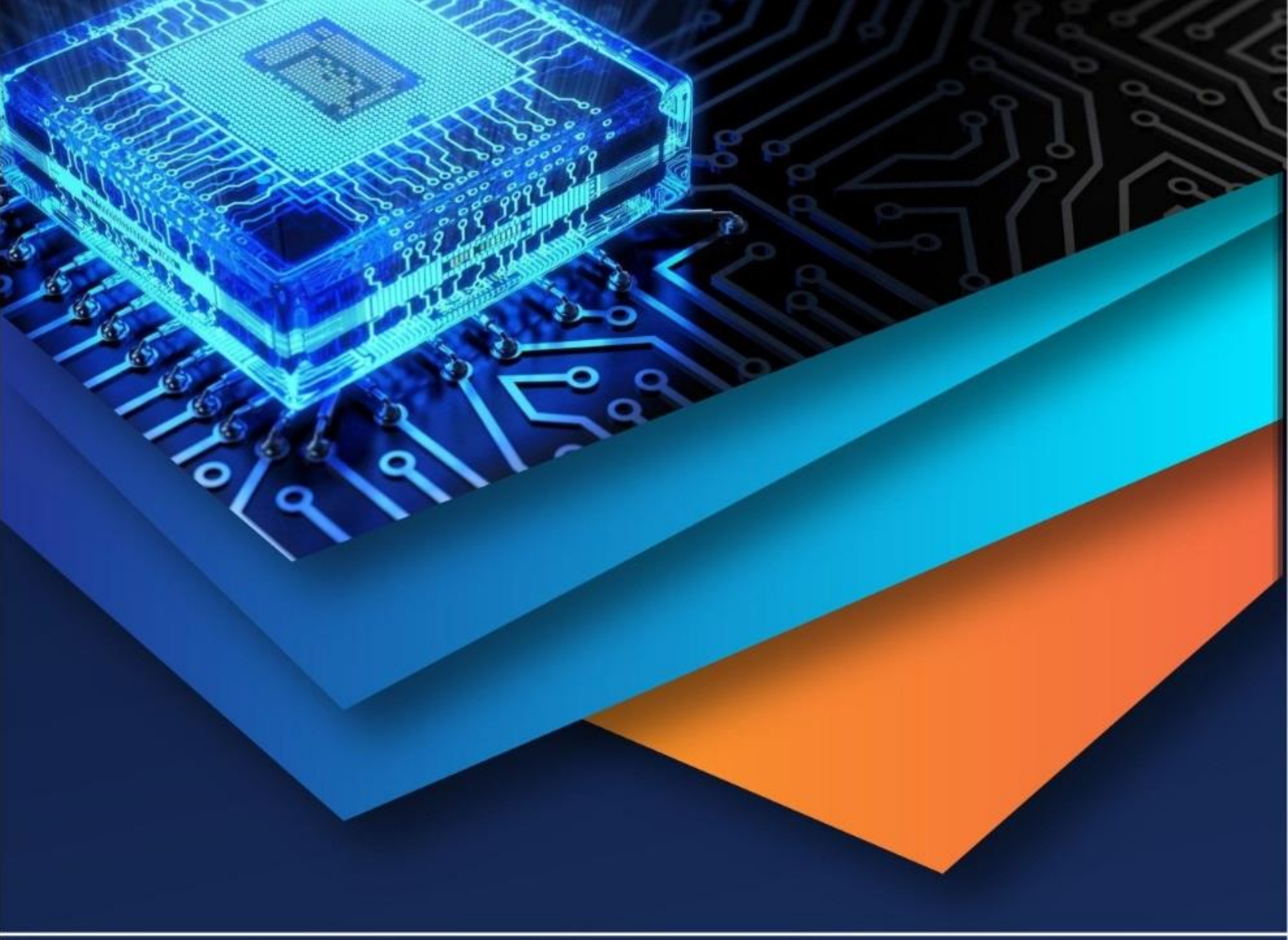
[9]P.Kontkanen, P.Myllymäki, T.Roos, H.Tirri, K.Valtonen and H.Wettig, "Probabilistic Methods for Location Estimation in Wireless Networks", *In Emerging Location Aware Broadband Wireless Ad Hoc Networks, Springer US*, pp. 173-188, 2005.

[10]P.Laube, S.Imfeld and R.Weibel,"Discovering relative motion patterns in groups of moving point objects", *International Journal of Geographical Information Science,* vol. 19,pp. 639–668,2005.

[11]S.Akoush and A.Sameh, "Mobile User Movement Prediction Using Bayesian Learning for Neural Network", *International conference on Wireless communications and mobile computing*, 2007.

[12] Y.Ishikawa," *Data Mining for Moving Object Databases,Mobile Computing and Computational Intelligence*", John Wiley & Sons , Chapter 12 (to appear), 2008.

[13] Y.Koren and J.Borenstein, "Potential Field Methods and Their Inherent Limitations for Mobile Robot Navigation", *Proceedings of the IEEE Conference on Robotics and Automation*, pp. 1398-1404, April 1991.



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